A Comparison between Hydrogeophysical Characterization Approaches Applied to Granular Porous and Fractured Media

Jinsong Chen, Susan Hubbard, and John Peterson

Earth Sciences Division, Lawrence Berkeley National Labortoray

This paper compares the use of geophysical data for subsurface characterization based on data collected at two different DOE field sites: the NABIR South Oyster site in Virginia and the Oak Ridge Field Research Center in Tennessee. The granular porous aquifer at the first site is relatively homogenous. At this site, petrophysical relationships between hydrogeological properties measured at wellbore locations and geophysical attributes could be developed using co-located wellbore and tomographic data. However, the aquifer at the second site is fractured and very heterogeneous, and reliable petrophysical relationships could not be developed using such co-located data sets. Different Bayesian models have been developed based on specific field conditions of the two sites to incorporate geophysical data into hydrogeological parameter estimation. Results show that despite the difference in aquifer heterogeneity, geophysical data provide useful information for hydrogeological characterization.

Introduction

Geophysical methods have found many applications in subsurface characterization (Hyndman et al., 1994; Hubbard and Rubin, 2000; Chen et al., 2001). The main reason for the success is that geophysical methods are less invasive and provide more information than traditional characterization methods. However, several obstacles still hinder the routine use of geophysics for hydrogeological characterization (Hubbard and Rubin, 2002).

One key obstacle is the lack of understanding of petrophysical relationships between geophysical attributes and hydrogeological parameters, especially in complex media such as fractured rock. In addition, the discrepancy in scale and resolution between geophysical and hydrogeological measurements, and uncertainty associated with geophysical data acquisition and interpretation make it difficult to develop petrophysical relations for linking geophysical attributes to hydrogeological properties. Consequently, applications of geophysical data for site characterization are often site-specific, and the petrophysical relationships are simple linear regression models obtained using co-located geophysical and hydrogeological data.

This study demonstrates the use of geophysical data for hydrogeological characterization at two DOE field sites that have dramatically different aquifer heterogeneity. We estimate the spatial distributions of hydraulic conductivity at the first site and hydrogeological zonation at the second site, using geophysical data and different Bayesian models. We discuss a comparison between the two Bayesian models developed according to site-specific petrophysical models.

Case Study at Granular Porous Media Site

Site information: The South Oyster Site is located near the town of Oyster on Virginia's Eastern Shore Peninsula between the Chesapeake Bay and the Atlantic Ocean. The sediments at the

South Oyster Site consist of unconsolidated to weakly indurated, well-sorted, medium- to fine-grained Late Pleistocene sands and pebbly sands. The water table at the site is located approximately 3 m below ground surface. Within the South Oyster Site, two study areas exist: the South Oyster Focus Area and the Narrow Channel Focus Area. This case study focuses on the Aerobic Flow Cell in the Narrow Channel Focus Area. Forced gradient chemical and bacterial tracer test experiments were performed within the flow cell in 1999 (Hubbard et al., 2001).

Extensive geophysical and hydrological data have been collected within the saturated portion of the Aerobic Flow Cell, approximately between depths of 0—6 m below the mean sea level (MSL), to characterize the subsurface before the tracer test experiments. These included ground-penetrating radar (GPR) and seismic tomographic data along each transect, and flowmeter and slug test data at 10 wellbores. Our goal was to provide detailed hydraulic conductivity estimates, by integrating crosswell geophysical data and borehole flowmeter data, which could be used to constrain numerical modeling of flow and contaminant transport at the site.

Data analysis: Hydraulic conductivity values obtained from wellbore flowmeter data displayed a small variation at this site; the natural logarithmic conductivity only had a variance of 0.30. The log-conductivity had a good spatial structure, which could be fit using an exponential model with a vertical range of 0.6 m and a horizontal range of 5 m. The geophysical tomographic data (including GPR and seismic velocity, and GPR attenuation), inverted from their corresponding travel time data, also varied over small ranges. The ranges of GPR velocity, GPR attenuation, and seismic velocity were 5.9—6.3 cm/ns, 0.18—0.38 1/m, and 1.61—1.73 km/s, respectively.

We developed petrophysical models between hydraulic conductivity and geophysical attributes using co-located hydraulic conductivity and geophysical data at the wellbore locations. Although both log-conductivity and geophysical data displayed small variations, good correlations exist between those parameters. Correlation coefficients of log-conductivity versus GPR velocity and log-conductivity versus seismic velocity were 0.68 and 0.67, respectively.

Estimation method: Since petrophysical models between the geophysical attributes and hydrogeological parameters could be developed, and log-conductivity had a good spatial structure, we developed a Bayesian model to integrate the geophysical data and borehole measurements. To illustrate this approach, we only use GPR velocity (for more types of geophysical data and details of the method, see Chen et al., 2001). Let v_i be the known GPR velocity at pixel-i (referred to as data). Let K_i be the unknown hydraulic conductivity at pixel-i (referred to as a random variable), which is spatially correlated to the hydraulic conductivity at its surrounding pixels. Thus, the Bayesian model is given as follows:

$$f(K_i \mid v_i) = C \bullet f(v_i \mid K_i) \bullet f(K_i) \,, \tag{1}$$

where C is a normalizing constant that insures integration of the left side is equal to one. The $f(K_i \mid v_i)$ term is referred to as the posterior probability density function (PDF), the $f(K_i)$ term is referred to as the prior PDF, and the $f(v_i \mid K_i)$ term is referred to as the likelihood function.

The posterior PDF in Equation 1 is obtained numerically. We first derive the prior PDF using geostatistical kriging of borehole hydraulic conductivity measurements. We then derive the likelihood function from the co-located log-conductivity and GPR velocity data at or near wellbores. For the given prior PDF and likelihood function, we divide the entire domain of prior distribution into many small intervals. For each data point on the domain, we evaluate the values of the prior PDF and likelihood function. Consequently, we obtain the posterior distribution of hydraulic conductivity at each point (0.25 m × 0.25 m pixel) in space along the 2D tomograms (Figure 1). Cross-validation suggests that this approach provides accurate estimates of hydraulic conductivity. The subsequent research also suggests that these data are very useful for constraining numerical models for flow and contaminant transport simulation (Scheibe and Chien, 2003) and for helping to understand bacterial transport in natural porous media (Malloux et al., 2003).

Case Study at the Fractured Media Site

Site information: The NABIR Research Field Center (FRC) is located on the Oak Ridge Reservation in Tennessee. The geology at this site is complicated. The Nolichucky shale bedrock under the site dips approximately 45 degrees to the southeast and has a strike of N55E. Overlying the bedrock is unconsolidated material that consists of weathered bedrock (referred to as residuum or saprolite), man-made fill, alluvium, and colluviums. The thickness of residuum is typically between 5 m and 10 m thick. Between the unconsolidated residuum and competent bedrock is a transition zone of weathered fractured bedrock. Remnant fracturing in the residuum and transition zone increases the permeability relative to the silt and clay matrix (Watson et al., 2003).

Several types of geophysical data have been collected at this site to characterize hydrogeological properties in the saturated, fractured media. Those data included surface seismic and electrical data, crosswell seismic and GPR data, various types of borehole geophysical logs, and flowmeter data. Our goal is to integrate crosswell geophysical tomographic data and borehole hydrogeological measurements to provide the spatial distribution of hydrogeological properties for understanding field-scale bioremediation experiments carried on this area.

Data analysis: Hydraulic conductivity at this site obtained from wellbore flowmeter data varied over a large range (3—4 orders of magnitude). Crosswell seismic tomographic data, gamma-ray logs, flowmeter data, and lithology logs collected at this site showed that two zones exist: the upper layer and the lower layer, with the interface at depths 8—10 m. The upper layer had lower hydraulic conductivity, high clay content, and low seismic velocity. The lower layer was fractured media with low clay content. Although crosswell GPR tomographic data were also collected along cross sections, the quality of GPR data was much lower than seismic data. We expect seismic data to be sensitive to the rock stiffness and thus the presence of fractures. Consequently, we choose to use crosswell seismic data only in the following analysis.

We developed petrophysical models for linking seismic tomographic data to hydraulic conductivity following a procedure similar to what was described in the preceding case study. The cross correlation between log-conductivity and seismic velocity, based on co-located data available at or near boreholes, was poor and thus could not be directly used to improve hydrogeological characterization. The weak correlation may be caused by difference of sampling volumes between crosshole seismic surveys and borehole flowmeter tests. Seismic methods sense seismic properties along a two-dimensional cross section, whereas flowmeter test senses hydraulic properties within a localized 3D volume around boreholes.

However, several other studies, including laboratory and field experiments, have shown that low seismic velocity in a fractured rock or media primarily is caused by the presence of fracture networks and thus can be used for hydraulic conductivity estimation (Pyrak-Nolte et al., 1987; Majer et al., 1997; Ellefsen et al., 2002; Daley et al., 2003). Accordingly, although we could not develop a good petrophysical relationship between hydraulic conductivity and seismic velocity based on co-located data at the wellbore, we believe that seismic velocity data could be useful for characterizing the fractured subsurface.

Estimation method: To incorporate seismic information into hydrogeological characterization, we improve the Bayesian model used in the first case study. It is necessary that the new model permit consideration of crosswell seismic velocity as unknown variables, which could be estimated by conditioning to both crosswell travel-time and borehole flowmeter data. This model should also allow for consideration of petrophysical models to be known up to unknown parameters, which are estimated during the joint inversion process.

Several assumptions are made and justified based on information available at this site. We estimate hydrogeological zonation (high or low conductivity zone) instead of continuous values of hydraulic conductivity. We assume that in the fractured media, the low seismic velocity is primarily caused by fracture networks. Therefore, high seismic velocity in this zone likely corresponds to low hydraulic conductivity, whereas low seismic velocity likely corresponds to high conductivity zone. However, since some fracture networks may not be connected and some clayey sandstone may also exist in the deeper part of the aquifer, the qualitative relationship described above is subject to uncertainty. To handle this uncertainty, we consider that the inverse of seismic velocity (slowness) at a specific location has the Gaussian distribution with mean and variance related to fracture density and thus hydraulic conductivity at each pixel.

The Bayesian model is developed based on seismic travel time and flowmeter data collected at two adjacent wells with the goal of estimating hydrogeological zonation along the 2D cross section passing through the two wells. The model can be directly applied to other wells for estimating hydrogeological zonation along other cross sections. Let t_j be the seismic travel time of the j-th raypath. Let K_i be the indicator of high conductivity zones (1—yes and 0—no) at pixel-i. Let S_i be the inverse of seismic velocity at pixel-i. Let vector θ be unknown parameters associated with petrophysical models. Variables σ_1 and σ_2 represent the standard deviations of travel time measurement errors and petrophysical model errors, respectively. The Bayesian model is given by:

$$f(\{K_i\},\{S_i\},\theta,\sigma_1,\sigma_2 \mid \{t_j\}) \propto \prod_j f(t_j \mid \{S_i\},\sigma_1) \bullet \prod_i f(S_i \mid K_i,\theta,\sigma_2) \bullet f(\{K_i\}) \bullet f(\theta) \bullet f(\sigma_1) \bullet f(\sigma_2)\,, \qquad (2)$$

where "∝" represents "proportional to". Therefore, Equation 2 is correct up to a normalizing constant, which is not needed for the method that we use for solving this problem.

Equation 2 is a coupled, complex statistical model, which considers both geophysical and hydrogeological parameters as random variables. Our goal is to estimate each individual unknown variable using the joint distribution function defined in Equation 2. The Bayesian model used in the first case study is a special case of this model. In that case, geophysical data at each pixel are considered as hard data, petrophysical relationships are known, and measurement errors of travel time are not been considered. Consequently, we decouple the estimation problem and solve it pixel by pixel. However, in this case, because many unknown variables are correlated and the number of variables involved is very large, conventional methods (such as analytical and optimization based methods) are limited. We use Markov chain Monte Carlo (Gilks et al., 1996) methods to solve all unknown variables. We generate many samples for each individual variable by running a constructed Markov chain from given starting values. From those samples, we obtain estimates of each unknown variable, including its mean, variance, and even probability density function. Estimation results (Figure 2) suggest that over the study area, a localized high permeability zone has laterally varying thickness and geological dip, which is consistent with observations of field tracer experiments.

Conclusions

The two case studies demonstrated that geophysical data are useful for providing information for hydrogeological characterization under varying degree of heterogeneity. However, for complex hydrogeological systems (such as fractured media), where regression based petrophysical models cannot be developed with confidence, sophisticated Bayesian models can be used. This model is more general because it allows physical based petrophysical relationships and forward models to be incorporated into the estimation process.

Acknowledgement

The authors wish to thank D. Watson, T. Mehlhorn, and P. Jardine at the Oak Ridge National Laboratory, and M. Fienen at Stanford University for providing flowmeter and geological data at the second case study. This research is supported by the DOE NABIR program.

References

Chen, J., S. Hubbard, and Y. Rubin, Estimating the hydraulic conductivity at the South Oyster site from geophysical tomographic data using Bayesian techniques based on the normal linear regression model, Water Resources Research, 37(6), 2001.

Daley, T., E. Majer, and J. Peterson, Crosswell seismic imaging in a contaminated basalt aquifer, Geophysics, in press.

Ellefsen, K., P. Hsieh, and A. Shapiro, Crosswell seismic investigation of hydraulically conductive, fractured bedrock near Mirror Lake, New Hampshire, Journal of Applied Geophysics, 50, 2002.

Gilks, W., S. Richardson, and D. Spiegelhalter, Markov Chain Monte Carlo in Practice, Chapman & Hall/CRC, New York, 1996.

Hubbard, S. and Y. Rubin, Hydrogeological parameter estimation using geological data: a review of selected techniques, Journal of Contaminant Hydrology, 45, 2000.

Hubbard, S. and Y. Rubin, Study institute assesses the state of hydrogeophysics, Eos Trans., 51, 2002.

Hubbard, S., J. Chen, J. Peterson, E. Majer, K. Williams, J. Swift, B. Mailloux, and Y. Rubin, Hydrogeological characterization of the South Oyster bacterial transport site using geophysical data, Water Resources Research, 37(10), 2001.
Hyndman, D., J. Harris, and S. Gorelick, Coupled seismic and tracer test inversion for aquifer property Characterization, Water Resources Research, 30(7), 1994.
Mailloux, B., M. Fuller, T. Onstott, J. Hall, H. Dong, M. DeFlaun, S. Streger, R. Rothmel, M. Green, D. Swift, and J. Radke, The role of physical, chemical, and microbial heterogeneity on the field-scale transport and attachment of bacteria, Water Resources Research, 39(6), 2003.
Majer, E., J. Peterson, T. Daley, B. Kaelin, J. Queen, P. D'Onfro, and W. Rizer, Fracture detection using crosswell and single well surveys, Geophysics, 62(2), 1997.
Peterson, J., Pre-inversion corrections and analysis of radar tomographic data, Journal of Environmental and Engineering Geophysics, 6, 1—18, 2001.
Pyrak-Nolte, L., L. Myer, N. Cook, and P. Witherspoon, Hydraulic and mechanical properties of a natural fractures in low permeability rock, Proceeding of the 6th International Congress on Rock Mechanics, edited by G. Herget and S. Vongpaisal, Balkema, Rotterdam, The Netherlands, 1987.
Scheibe, T., and J. Chien, An evaluation of conditioning data for solute transport prediction, Ground Water, 41(2), 128—141, 2003.
Watson, D., W. Doll, T. Gamey, J. Sheehan, and P. Jardine, Demonstration and interpretation of improved geophysical profiling methods at the DOE NABIR Field Research Center, Ground Water, in press.

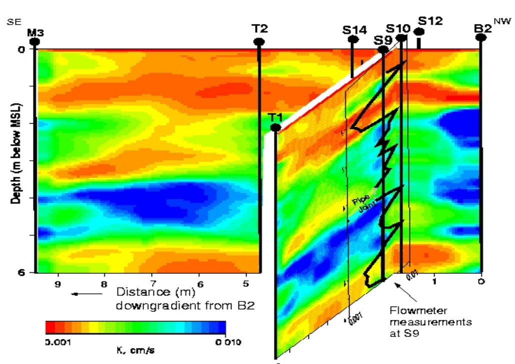

Figure 1. Estimated mean log-conductivity along geological dip and strike directions at the granular porous media site

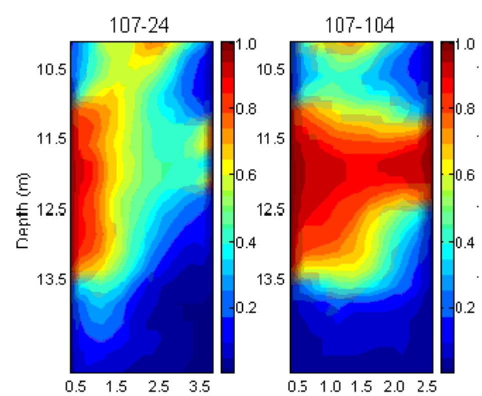

Figure 2. Estimated probability of high permeability zonation along two transects at the fractured media site